Cross-fertilising research in nonlinear system identification between the mechanical, control and machine learning fields

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Cross-fertilising research in nonlinear system identification between the mechanical, control and machine learning fields ☆

Editorial statement

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1. Introduction

Nonlinear system identification, or nonlinear data-driven modelling, is a discipline attracting attention from a wide array of research fields. This is particularly true for the mechanical, control and machine learning fields, three communities historically involved into research on data-driven modelling of nonlinear dynamic systems. In mechanics, the first works addressing the identification of nonlinear models from data date back to the 1970s, one of the seminal contributions being the highly cited paper by Masri and Caughey [1]. Over the years, substantial progress has been achieved from both the theoretical and experimental points of view, with the publication of a myriad of techniques addressing the many challenging facets of nonlinear mechanical systems identification [2].

Surprisingly perhaps, this long and fruitful evolution has remained rather insensitive to developments that have taken place concurrently within sister communities. In particular, in control engineering, nonlinear system identification has received significant attention for many decades. It is interesting here to quote Gevers who, in his historical perspective in Ref. [3], wrote that “Identification theory for nonlinear systems is almost as old as identification theory for linear systems”. A few of the most salient contributions to the identification of nonlinear systems to be found in the control engineering literature are arguably related to black-box model structures and their estimation [4]. In a similar manner, for many years now in the machine learning field, powerful mapping methods for representing nonlinear dynamic systems have been studied [5], providing inspiring ideas to researchers active in nonlinear data-driven modelling.

☆ Editorial statement of a special issue on “Cross-fertilising research in nonlinear system identification between the mechanical, control and machine learning fields”.

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Although the boundaries surrounding the mechanical community may appear to be rather opaque to knowledge transfer, they have been crossed by a number of notable research groups. Billings and co-workers popularised the NARMAX model structure, originating from time series analysis and control engineering, and that has found many successful applications to mechanical problems since then [6]. Taking its roots in the electrical engineering field, the Volterra series theory forms the basis of many nonlinear system identification approaches published in mechanical journals [7]. Another popular tool, borrowed this time from the machine learning literature, is the artificial neural network, extensively utilised in mechanics since the early 1990s [8,9]. In this latter respect, a recommended reading is the excellent review paper [10] by Worden and co-authors, where it is discussed how mechanical systems research could benefit from the new concepts and algorithms emerging these years in machine learning.

We strongly believe that encouraging the exchange of ideas across research communities is mutually rewarding. With this in mind, the Workshop on Nonlinear System Identification Benchmarks (NSIB) was created in 2016, with the prime objective to offer a yearly forum bringing together researchers interested in any scientific aspect related to nonlinear system identification and modelling, and who otherwise have very few occasions to interact. The present Special Issue (SI) promotes this cross-fertilisation goal by making the regular MSSP readership aware of some of the data-driven nonlinear modelling tools that are being developed by members of the systems and control or machine learning communities.

This Editorial note is organised as follows. Section 2 introduces the three benchmark systems that form the backbone of the SI, together with the challenges they pose to the current state of the art in nonlinear system identification. The associated data sets are available for download at www.nonlinearbenchmark.org. In Section 3, a description of the content of the ten papers contributing to the SI is given. Though the material reported in this SI is inspired by oral presentations that were delivered during the first edition of the NSIB Workshop, all the presented papers were written so as to meet Journal Publication standards. The first NSIB Workshop was held at the Vrije Universiteit Brussel, Brussels, Belgium, from 25 to 27 April 2016. Since then, two other editions of the Workshop were organised, at the Vrije Universiteit Brussel again in 2017 and at the University of Liège, Belgium, in 2018. A fourth edition will be held at the Eindhoven University of Technology, The Netherlands, in 2019.

2. Three benchmark systems

Benchmarking plays a central role in research fields experiencing very rapid growth by providing standard problems through which the performance of various solution approaches can be fairly evaluated and compared. The NSIB Workshops, and so is this SI, are structured around three state-of-the-art benchmark systems. They are motivated and described in the following sections.

2.1. Bouc-Wen benchmark with a dynamic nonlinearity

The first benchmark problem relies on synthetic, noisy data exhibiting hysteresis and generated by combining the Bouc-Wen differential equations and the Newmark integration rules. The defining property of a hysteretic system is the persistence of an input-output loop as the input frequency approaches zero [11]. Hysteretic systems are inherently nonlinear, as the quasi-static existence of a loop requires an input-output phase shift different from 0 and 180 degrees, the only two options offered by linear theory. The root cause of hysteresis is multistability [12]. A hysteretic system possesses multiple stable equilibria, attracting the output depending on the input history. In this sense, it is appropriate to refer hysteresis as system nonlinear memory.

2.1.1. The Bouc-Wen model of hysteresis

The Bouc-Wen model [13,14] has been intensively exploited for a long time in mechanical engineering to represent hysteretic effects, especially in the case of random vibrations. The dynamic behaviour of a single-degree-of-freedom Bouc-Wen system, *i.e.* a Bouc-Wen oscillator with a single mass, is governed by Newton's second law written in the form [14]

$$m\ddot{y}(t) + r(y, \dot{y}) + z(y, \dot{y}) = u(t), \quad (1)$$

where m is the mass constant, y the displacement, u the external force, and where an overdot indicates a derivative with respect to the time variable t . The total restoring force in the system is composed of a static nonlinear term $r(y, \dot{y})$, which only depends on the instantaneous values of the displacement $y(t)$ and velocity $\dot{y}(t)$, and of a dynamic, *i.e.* history-dependent, nonlinear term $z(y, \dot{y})$, which encodes the hysteretic memory of the system. In the present case, the static restoring force contribution is assumed to be linear, that is

$$r(y, \dot{y}) = k_L y + c_L \dot{y}, \quad (2)$$

Table 1

Physical parameters of the Bouc-Wen system.

Parameter	m	c_L	k_L	α	β	γ	δ	ν
Value (in SI unit)	2	10	$5 \cdot 10^4$	$5 \cdot 10^4$	$1 \cdot 10^3$	0.8	−1.1	1

Table 2

Linear modal parameters of the Bouc-Wen system.

Parameter	Natural frequency (Hz)	Damping ratio (%)
Value	35.59	1.12

Fig. 1. Hysteresis loop in the system input-output plane for quasi-static forcing conditions. (a) Non-degenerate loop obtained for the parameters in Table 1; (b) linear behaviour retrieved when setting the β parameter to 0.

where k_L and c_L are the linear stiffness and viscous damping coefficients, respectively. The hysteretic force $z(y, \dot{y})$ obeys the first-order differential equation

$$\dot{z}(y, \dot{y}) = \alpha \dot{y} - \beta \left(\gamma |\dot{y}| |z|^{v-1} z + \delta \dot{y} |z|^v \right), \quad (3)$$

where the five Bouc-Wen parameters $\alpha, \beta, \gamma, \delta$ and v are used to tune the shape and the smoothness of the system hysteresis loop. Table 1 lists the values of the physical parameters considered herein. The linear modal parameters deduced from m, c_L and k_L are given in Table 2. Fig. 1(a) illustrates the existence of a non-degenerate loop in the system input-output plane for quasi-static forcing conditions. In comparison, by setting the β parameter to 0, a linear behaviour is retrieved in Fig. 1(b). The excitation $u(t)$ in these two figures is a sine wave with a frequency of 1 Hz and an amplitude of 120 N. The response exhibits no transients as it is depicted over 10 cycles in steady state.

2.1.2. Time integration

The Bouc-Wen dynamics in Eqs. (1) and (3) can be effectively integrated in time using a Newmark method. Newmark integration relies on one-step-ahead approximations of the velocity and displacement fields obtained by applying Taylor expansion and numerical quadrature techniques. Denoting by h the integration time step, these approximation relations write

$$\begin{aligned} \dot{y}(t+h) &= \dot{y}(t) + (1-a)h\ddot{y}(t) + ah\ddot{y}(t+h) \\ y(t+h) &= y(t) + h\dot{y}(t) + \left(\frac{1}{2}-b\right)h^2\ddot{y}(t) + bh^2\ddot{y}(t+h). \end{aligned} \quad (4)$$

Parameters a and b are typically set to 0.5 and 0.25, respectively. Eq. (4) are herein enriched with an integration formula for the variable $z(t)$, which takes the form

$$z(t+h) = z(t) + (1-c)h\dot{z}(t) + ch\dot{z}(t+h), \quad (5)$$

where c , similarly to a , is set to 0.5. Based on Eqs. (4) and (5), a Newmark scheme proceeds in two steps. First, predictions of $\dot{y}(t+h)$, $y(t+h)$ and $z(t+h)$ are calculated assuming $\ddot{y}(t+h) = 0$ and $\dot{z}(t+h) = 0$. Second, the initial predictors are corrected via Newton-Raphson iterations so as to satisfy the dynamic equilibria in Eqs. (1) and (3).

The reader interested in generating Bouc-Wen benchmark data is strongly advised to read the practical guidelines towards accurate time integration available at www.nonlinearbenchmark.org. Note that Gaussian noise band-limited in 0–375 Hz is automatically added to the synthesised measurement of $y(t)$ considering a root-mean-squared (RMS) amplitude of $8 \cdot 10^{-3}$ mm. This provides a realistic signal-to-noise ratio of about 40 dB at 50 N excitation level. The input time series $u(t)$ is assumed to be noiseless.

On the webpage mentioned above are also provided two example data sets that may function as targets for the identified models. They are noiseless and were generated under random phase multisine and sine-sweep excitation signals considering a sampling frequency of 750 Hz. The random phase multisine data set contains one steady-state period of 8192 samples. The excited band encompasses all frequencies in 5–150 Hz, and the RMS input value is 50 N. The sine-sweep data set is not in steady state, the simulation started with initial conditions equal to zero. In this case, the amplitude of the input is 40 N, and the frequency band from 20 to 50 Hz is covered at a sweep rate of 10 Hz/min.

2.1.3. Nonlinear system identification challenges

The Bouc-Wen benchmark is expected to be associated with four major identification challenges, namely:

- it possesses a nonlinearity featuring memory, i.e. a dynamic nonlinearity;
- the nonlinearity is governed by an internal variable $z(t)$ which is not measurable;
- the nonlinear functional form in Eq. (3) is nonlinear in the parameter v ;
- the nonlinear functional form in Eq. (3) does not admit a finite Taylor series expansion because of the presence of absolute values.

2.2. Wiener-Hammerstein benchmark with process noise

The second benchmark problem consists in a real Wiener-Hammerstein electronic circuit, featuring process noise as the dominant distortion source. The process noise problem is well understood in the linear time-invariant (LTI) framework, where it is solved satisfactorily using nonparametric and parametric noise representations, like the Box-Jenkins, ARX or ARMAX models [15,16]. By contrast, most of the nonlinear modelling approaches only consider additive, potentially coloured, noise at the output (see, for example, the methods listed in Refs. [17,18]), or are restricted to ARX- or NARX-like noise models [6,19]. Some more complex noise frameworks were addressed recently using expectation maximisation, particle filter or errors-in-variables techniques [20–22].

2.2.1. The Wiener-Hammerstein circuit

The Wiener-Hammerstein structure is a well-known block-oriented system. It contains a static nonlinearity sandwiched in between two LTI blocks, as schematised in Fig. 2. The combined presence of these blocks leads to a problem that is harder to identify than the more fundamental Wiener and Hammerstein systems. The system in Fig. 2 is similar to the Wiener-Hammerstein benchmark proposed earlier in Refs. [23,24], except for the introduction of process noise.

The first LTI block $R(s)$ can be described well with a third-order, low-pass filter. The second LTI subsystem $S(s)$ is designed as an inverse Chebyshev filter with a stop-band attenuation of 40 dB and a cut-off frequency of 5 kHz. It should be stressed that $S(s)$ possesses a transmission zero within the excited frequency range, making its inversion difficult. The static nonlinearity $f(x)$ is realised with a diode-resistor network, resulting in a saturation nonlinearity. Finally, the additive process noise $e_x(t)$ is a filtered white Gaussian noise sequence. It is generated starting from a discrete-time, third-order low-pass Butterworth filter followed by a zero-order-hold reconstruction and an analogue low-pass reconstruction filter with a cut-off frequency of 20 kHz. The disturbance sources $e_u(t)$ and $e_y(t)$ account for input and output measurement noise, respectively, and can be considered to be white Gaussian signals. They are very small in magnitude, and are substantially dominated by the process noise source $e_x(t)$.

2.2.2. Experimental test campaigns

The participants of the NSIB Workshop 2016 were given the opportunity to design bespoke estimation input signals, and measurements were accordingly conducted at the ELEC Department of the Vrije Universiteit Brussel by an experienced user.

Fig. 2. Wiener-Hammerstein benchmark system with a process noise source.

Fig. 3. Realisation as an electronic circuit of the Wiener-Hammerstein benchmark with process noise.

A picture of the real setup is displayed in Fig. 3. The collected data sets are available at www.nonlinearbenchmark.org, and consist primarily of various sine, multisine and sine-sweep experiments. Two target data sets based on random phase multisine and sine-sweep inputs are also provided, similarly to the Bouc-Wen benchmark. These two data sets contain one signal period acquired in steady-state conditions. In both experiments, the RMS input value is 0.71 V, and the excited frequencies span the 0–15 kHz interval, DC excluded. The sine-sweep excitation covers this band at a sweep rate of 4.29 MHz/min. It is important to finally note that the two target data sets were measured in the absence of process noise. They can therefore serve to verify noise assumptions, that typically lead to biased parameter estimates when violated [25].

2.2.3. Nonlinear system identification challenges

The three following challenges are specifically believed to make the identification of the Wiener-Hammerstein benchmark arduous:

Fig. 4. Cascaded tanks benchmark system.

- it exhibits a dominant process noise source;
- the system nonlinearity is not accessible from either the measured input or output;
- the output dynamics are difficult to invert due to the presence of a transmission zero.

2.3. Cascaded tanks benchmark with combined nonlinearities

The third and final benchmark problem is an experimental fluid level control system consisting in two vertically assembled water tanks with free outlets. The input to the system controls the pumping of water from a reservoir into the upper tank. Through small openings, water flows first from the upper to the lower tank, and eventually back into the reservoir. This physical process is pictured in Fig. 4. It can be shown from first-principle laws that the relations between the water levels and the system input are weakly nonlinear, ordinary differential equations. However, when the amplitude of the input signal is too large, the upper water tank can overflow, potentially followed with a delay by a lower tank overflow. In the case of an upper tank overflow, part of the excess water goes into the lower tank, the rest being directly collected in the reservoir. This effect is very difficult to predict and can hence be seen as a stochastic phenomenon, acting on the system as an input-dependent process noise source. The saturation-type nonlinearity induced by the overflow behaviour is clearly visible in the time-domain representation of the output signals in Fig. 5(b) below. A video of such an overflow can also be found on the NSIB Workshop webpage.

Neglecting the overflow effect, the following input-output model can be constructed based on Bernoulli's and mass conservation principles:

$$\begin{aligned}\dot{x}_1(t) &= -k_1 \sqrt{x_1(t)} + k_4 u(t) + w_1(t) \\ \dot{x}_2(t) &= k_2 \sqrt{x_1(t)} - k_3 \sqrt{x_2(t)} + w_2(t) \\ y(t) &= x_2(t) + e(t),\end{aligned}\tag{6}$$

where $u(t)$ is the input, $x_1(t)$ and $x_2(t)$ are the system states, $w_1(t)$, $w_2(t)$ and $e(t)$ are additive noise sources, and k_1, k_2, k_3 and k_4 are constant parameters depending on the system physical properties.

2.3.1. Experimental test campaigns

Estimation and test data sets are available at www.nonlinearbenchmark.org. The estimation and test input signals are zero-order-hold random phase multisines, containing 1024 points and exciting frequencies from 0 to 0.0144 Hz. Note that

Fig. 5. Input (a,c) and output (b,d) signals of the estimation (blue) and test (red) data records in the time (a,b) and frequency (c,d) domain. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

lower frequencies have a higher amplitude, as shown in Fig. 5(c). The sampling frequency is equal to 4 Hz. The process is controlled from a Matlab interface to the A/D and D/A converters attached to the water level sensors and pump actuator. Output measurements are obtained with capacitive level sensors, with a signal-to-noise ratio close to 40 dB. The water level sensors are considered to be part of the system, they are not calibrated and can introduce an extra source of nonlinear behaviour. To conclude, it should be remarked that the system was not in steady state during the measurements. The system states have therefore unknown initial values, though they are the same for the estimation and test data records.

2.3.2. Nonlinear system identification challenges

The nonlinear identification of the cascaded tanks benchmark is expected to be challenging primarily because of:

- the hard saturation nonlinearity caused by potential overflows combined with the weakly nonlinear behaviour observed in normal operation;
- the input-dependent process noise contribution induced by the upper tank overflow;
- the relatively short estimation data length;
- the unknown initial value of the system states.

3. Special Issue contributing papers

The present SI features ten contributions, including two overview papers and eight regular papers. They are all based upon presentations that were given during the 2016 NSIB Workshop.

3.1. Overview papers

The first two contributions present didactic overviews of two popular machine learning-based identification methodologies. The paper by Worden and co-authors first discusses the question “Is system identification simply machine learning?”. It continues with a study of the use of evolutionary optimisation as a basis for a general nonlinear modelling framework. The power of this framework is illustrated on the three benchmark systems. In the paper by Schön and co-authors, the use of Monte-Carlo techniques for the identification of dynamic systems is surveyed, providing a self-contained introduction to the particle Metropolis-Hastings algorithm. It is explained in detail how this approach allows one to obtain probabilistic models of nonlinear systems.

3.2. Regular papers

The remaining eight regular papers can be classified into three specific families, namely “from linear to nonlinear system identification”, “introducing structure in nonlinear system identification”, and “machine learning methods for nonlinear system identification”.

3.2.1. From linear to nonlinear system identification

The behaviour and identification of linear systems is much better understood and mature than that of nonlinear systems. This motivates authors to extend well-established linear system identification techniques towards nonlinear problems. The paper by Bajrić and Høgsberg generalises an output-only linear identification approach to an output-only modal parameter identification method for hysteretic systems. Mattson and co-authors study the identification of piecewise linear ARX models as a nonlinear extension of the classical linear model class.

3.2.2. Introducing structure in nonlinear system identification

Classifying nonlinear system identification methods involves many shades of grey [26], with a wide variety of model structures ranging from pure white-box to full black-box. In this context, the paper by Giordano and Sjöberg compares the quality of the models obtained by standard black-box identification techniques with the one of models derived in a physics-based, white-box perspective. In the two contributions by Esfahani and Relan and their co-authors, a nonlinear black-box approach is utilised to identify one of the proposed benchmark systems. In a second step, the two papers study the introduction of more structure in the derived black-box models to reduce their number of parameters.

3.2.3. Machine learning methods for nonlinear system identification

The three final contributing papers illustrate the application of powerful machine learning methods in a nonlinear system identification setting. Svensson and his co-authors use particle filter-based approaches to obtain nonlinear probabilistic models, proposing a new method to handle the case of highly informative measurements. The advantages of kernel-based regression techniques are analysed in the papers by Birpoutsoukis and co-authors and by Rébillat and Schoukens. It is illustrated how kernel-based regression avoids ill-conditioning issues by including prior knowledge on the parameters. For dynamic systems, such prior knowledge can take the form of frequency band or stability information.

In conclusion, we wish to thank the authors for their contributions, and all the reviewers who invested time and effort in rigorously assessing the papers published in this SI.

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